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AUTOMATED PROCESSING OF SATELLITE IMAGERY DATA AT AIR FORCE GLOBAL WEATHER CENTRAL (AFGWC): DEMONSTRATIONS OF SPECTRAL ANALYSIS

Elliot S. Blackman
Ronald M. Pickett

Bolt Beranek and Newman Inc.

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This document is the final report of a one year program of work concerned with finding ways to upgrade automated processing of Defense Meteorological Satellite Program (DMSP) imagery data at Air Force Global Weather Central (AFGWC). In the first of two states of work, surveys were conducted to identify needs for imagery processing at AFGWC and to find the best technique for AFGWC to adopt next in upgrading its capability for automated imagery processing. The over

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procedure and results of the first stage, including the recommendation that spectral analysis be adopted for improved feature abstraction in the current 3DNEPH program, are separately reported. The procedure and results of Stage 2, which focused on demonstrations and checks of spectral analysis on selected DMSP imagery samples, are presented here along with a summary of conclusions and recommendations from the contract effort as a whole.

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1. INTRODUCTION

This document is the final report of work conducted under support of Contract F19628-76-C-0124. The contract was concerned with finding techniques to improve automated, realtime processing of Defense Meteorological Satellite Program (DMSP) imagery data at Air Force Global Weather Central (AFGWC), Offutt AFB, Nebraska. The work was conducted in two stages. In the first stage, surveys were carried out: 1) to determine AFGWC needs for DMSP imagery processing; 2) to find current state of the art techniques in automated imagery processing relevant to meeting those needs; and 3) to recommend one or more techniques that would be most promising for AFGWC to adopt next in its continuing effort to upgrade its capabilities in this critical area of meteorological data processing. In the second stage the recommended technique was demonstrated on selected samples of DMSP imagery.

The procedures and results of Stage 1 have been separately reported (Pickett and Blackman, 1976). The rationale, procedures and results of Stage 2 along with summary and conclusions for the contract effort as a whole are the primary subjects of this report.

2. BACKGROUND

For background to the presently reported work, we present first a brief sketch of the conclusions and recommendations from the work in Stage 1. Issues that shaped our approach to Stage 2 are discussed, and the resulting structure and emphasis of the work are described.

2.1 Results of Stage 1

The work in Stage 1 resulted first in two general conclusions and related recommendations. The first conclusion to be drawn was that in those areas, such as the forecasting area, where imagery processing is entirely visual, needs for automation cannot be adequately determined without conducting systems analyses and information flow studies falling well beyond the scope of the present contract. It was recommended that such studies be undertaken.

The second conclusion was that AFGWC lacked a fully adequate long term strategy for developing an automated system, particularly in terms of expanding its capabilities to encompass processing now done visually. It was recommended that such a long term strategy be developed, one that allows for the integration of visual and automated processing, probably through interactive computer techniques, to provide the basis for an evolutionary approach to full automation.

As a consequence of these two conclusions, it was decided early in the contract schedule that the most productive effort would be one that focused on AFGWC's present approach and thrust in automated imagery processing as represented in the currently operating 3DNEPH program. Analyses showed that there is a clear and pressing need there to improve imagery analysis at the feature abstraction stage, to upgrade capability at the front end of the system where those features that get passed on to the pattern recognition component get culled from the full data stream. For several statistical and practical reasons, spectral analysis was recommended as the most promising technique for improved feature abstraction.

2.2 Issues Shaping the Work in Stage 2

The point of the second stage of work was to conduct a feasibility analysis of the recommended technique: first to demonstrate its consistency with AFGWC needs, in other words, to show its usefulness to AFGWC; and second to show feasibility of its being interfaced with AFGWC data analysis systems present and proposed. How that goal was to be achieved within the limited contract time and resources reserved for it was to depend very largely on the particular technique that was recommended. Our approach with respect to the particular recommendation of using spectral analysis for improved feature abstraction was affected by two main considerations.

The first consideration was that little more could be done from an analytical standpoint to demonstrate the usefulness of spectral features for cloud classification than had already been done in Stage 1. As our surveys revealed, there are no extant mathematical/statistical models, or even an adequate body of structural descriptions for telling what features of satellite images are critical for distinguishing among cloud classes. Part of AFGWC's long term strategy for automation certainly should be to look recurrently for such aids and provide for ways to integrate them into the system as they become available. In the meantime, however, there is really no adequate way to tell how useful a particular algorithm for feature abstraction will be without conducting empirical studies, and those studies have to be substantial enough to permit valid generalization of the findings to field operations. Such studies have to be made on samples of imagery for every cloud class that occurs with appreciable frequency, in order to test for all potentially significant errors of classification. And for every one of those classes, the sample has to be sufficiently large and well drawn to be validly representative of that class. It is not just the numbers of imagery samples required that define the magnitude of the effort involved, it is also the need for adequate care in determining the "true" classification of each image. Various options are open for reducing the magnitude of such studies, e.g. by explicitly restricting the geographical or seasonal domain of sampling, or by restricting the domain of explicitly tested classifications, but even a highly pared version of such a study is clearly beyond the scope of this contract effort. It was decided, therefore, to focus the work in Stage 2 on the second and more limited aspect of feasibility--determining whether spectral analysis was compatible with AFGWC data analysis systems. It certainly was possible within the remaining contract effort to demonstrate spectral analysis of DMSP imagery taken from the AFGWC data analysis system. A demonstration of compatibility at that level was set as the minimum goal for Stage 2.

The second consideration was that as a result of our first report and related briefings, AFGWC decided to undertake a large-scale empirical study of the type needed for an adequate test of spectral analysis. It was decided that AFGL would assist in this endeavor by providing a computer programmer to do the encoding necessary to get spectral analysis up and running on the AFGWC data analysis system. The test was to be conducted as soon as the necessary computer coding, experimental designing and data sampling could be achieved. The test was to be designed to assess the impact of spectral analysis on accuracy of cloud classification in the 3DNEPH context.

In view of that decision, it was determined that BBN should coordinate its activity in Stage 2 with that of the AFGL programmer. The intent was to insure, insofar as possible, that all computer coding for BBN's demonstrations and tests would be directly transferable to the AFGWC data analysis system. Thus, a smooth connection was sought between BBN's work in Stage 2 and that work on the large-scale empirical study.

Subsequent to setting these goals, a decision was made to add an item of work to the contract concerned with estimating spatial power spectral characteristics of a range of pure cloud types. The point of this activity was that it might provide useful leads in the search for discriminating spectral features. The plan was to arrive at purely qualitative characterizations of the power spectra based on visual inspection of typical examples of pure cloud types as given by Conover (1962). Thus, this activity was added to the work in Stage 2.

2.3 Structure and Emphasis of Work in Stage 2

The main emphasis of work in Stage 2 was on guiding implementation of spectral analysis and in conducting selected checks and demonstrations on DMSP imagery data.

As regards the added item of work, an effort was made to determine power spectra for a range of cloud types, but it was judged that that was not feasible. First, the intent of that effort was that the estimates be obtained from purely visual inspection of available cloud imagery samples (as given, e.g., by Conover, 1962) in comparison to standard test patterns for which spectra had already been computed. Detailed consideration of that approach led to the conclusion that there was an insufficient body of visually comparable standard test patterns in the literature, for which spectra had been computed, to permit such purely visual estimates. Second, consideration was given to the possibility of computing spectra on the imagery samples given by Conover but this also was judged to be not justified, even by optical means, for two main reasons. First, there was no way to guarantee that spectral signatures obtained for those imagery samples would generalize to the DMSP images taken at different altitudes, by different sensors, and subjected to corrections not common to the Conover images. Second, it was judged that any leads on critically discriminating spectral features, obtained from comparison of spectra based on just the few samples provided by Conover, would be very suspect. Estimates of error of the spectral signature would have to be available to obtain leads with any acceptable degree of reliability. Better, it was judged, to wait for data obtained in the large scale empirical study. Thus, the effort to estimate spectra was carried only to the point where it was judged to be infeasible, and greater time was spent on the main line of activity.

One aspect of the main Stage 2 effort which required more attention than was originally supposed, was communication with AFCWC, particularly in planning the large scale empirical study. Joint planning was necessary for BBN to provide adequate guidance to the AFGL programmer and for BBN to coordinate its demonstrations and checks of spectral analysis, as far as possible, with AFGWC's preparations.

3. DEMONSTRATIONS OF SPECTRAL ANALYSIS ON SELECTED SAMPLES OF DMSP IMAGERY DATA

Implementation of spectral analysis in code compatible with AFGC data analysis systems was primarily the responsibility of AFGL. BBN has contributed advice and direction to that work, and modified certain of the reported approaches (Booth, 1973, Sikula, 1974), particularly as regards the computation of wave number spectra. Setting up, overseeing and interpreting the demonstration of spectral analysis on selected samples of DMSP imagery data was BBN's other primary responsibility.

In this section, we discuss first the rationale behind and the logic of implementing spectral analysis and spectral feature-based classification. We then present the procedure and results of demonstrations and tests on selected samples of DMSP imagery data.

3.1 Rationale

Clearly, the immediate point of implementing and checking spectral analysis in this effort was to enable AFGWC to proceed with direct tests of its utility--perhaps as the key to a stand alone satellite data processor--via the planned large scale empirical study. But the primary importance of developing power spectral analysis within the 3DNEPH framework is not simply to build, immediately, a better processor. More important, it is to assess the potential value of going in this direction of signal processing, to gauge the long run benefits and costs, improvements and limitations of this next level of processing capability. The operational success of using spectral features for classification depends foremost on the presence of information in the recorded data stream; no transformation of that data can create the required information if it is absent. For certain classification tasks, HR data may provide sufficiently fine detail, while for other tasks even VHR data may not have adequate resolution. Similarly, information required for classification may be contained separately or jointly in the visible and infrared (IR) spectral regions, or it may reside in a region (e.g., microwave) not presently sensed. Identifying and understanding processor behavior in cases such as these as they occur in the operational scenario will provide guidance towards the continuing improvement of the satellite data processor.

3.2 Implementation

The conversion of raw data to labeled cloud type will involve the computation of power spectra, conversion of these data to wave number spectra (as discussed below) and computation of a statistic sufficient for classification.

3.2.1 Two-Dimensional Spectra and the Fast-Fourier Transform(FFT)

The Discrete Fourier Transform (DFT) in two dimensions is defined as

$$\hat{a}\,(f_x,f_y) = \sum_{j=1}^{N} \sum_{k=1}^{M} a\,[j(\Delta x),\, k(\Delta y)]\; e^{-i2\Pi\,[jf_x(\Delta x) + kf_y(\Delta y)]} \tag{1}$$

with $\hat{a} \leftrightarrow a$ representing Fourier transform pairs.

If we let $N=M$, $\Delta x = \Delta y = T/N$ (with T the analysis window size), and compute f_x, f_y only at integer multiples of T^{-1}, then

$$\hat{a}\,(n,m) = \sum_{j=1}^{N} \sum_{k=1}^{N} a\left(\frac{jT}{N},\, \frac{kT}{N}\right) e^{\frac{-i2\Pi}{N}\left(jn + km\right)} \tag{2}$$

which is the defining form of the FFT. The inverse FFT need not concern us here because it will not be used below. Note that for n=m=0, we have

$$\hat{a}\,(o,o) = \sum_{j=1}^{N} \sum_{k=1}^{N} a\left(\frac{jT}{N}, \frac{kT}{N}\right) \tag{3}$$

which is the sum over the data and therefore N^2 times the average value over the TxT data window. When computing wave number spectra, we may prefer to normalize Equation 2 by dividing by N^2 so that the value of the spectrum at (0,0) will be the data average. Although we have taken this option in our initial work, there is a basic normalization dichotomy for deterministic vs. random processes. Involved here is a conflict between coherent and incoherent summation. Further discussion is deferred to the section treating processing results.

Computing Equation 2 using the FFT algorithm produces an array of data representing the first quadrant in the two dimensional spectral plane. Because of the spectrally periodic nature of the FFT, the entire spectral plane can be generated from first quadrant data, allowing direct computation of wave number spectra. Figure 1 shows schematically a 16x16 array comprising the original 8x8 (upper righthand corner) array of data, periodically extended. The numbers in the arrays may be considered as the indices (relative frequencies) in a FORTRAN array dimensioned (0/7, 0/7), with the comma separating the indices implied. That is, the number 70 would refer to location

70	71	72	73	74	75	76	77	70	71	72	73	74	75	76	77
60	61	62	63	64	65	66	67	60	61	62	63	64	65	66	67
50	51	52	53	54	55	56	57	50	51	52	53	54	55	56	57
40	41	42	43	44	45	46	47	40	41	42	43	44	45	46	47
30	31	32	33	34	35	36	37	30	31	32	33	34	35	36	37
20	21	22	23	24	25	26	27	20	21	22	23	24	25	26	27
10	11	12	13	14	15	16	17	10	11	12	13	14	15	16	17
00	01	02	03	04	05	06	07	00	01	02	03	04	05	06	07
70	71	72	73	74	75	76	77	70	71	72	73	74	75	76	77
60	61	62	63	64	65	66	67	60	61	62	63	64	65	66	67
50	51	52	53	54	55	56	57	50	51	52	53	54	55	56	57
40	41	42	43	44	45	46	47	40	41	42	43	44	45	46	47
30	31	32	33	34	35	36	37	30	31	32	33	34	35	36	37
20	21	22	23	24	25	26	27	20	21	22	23	24	25	26	27
10	11	12	13	14	15	16	17	10	11	12	13	14	15	16	17
00	01	02	03	04	05	06	07	00	01	02	03	04	05	06	07

Figure 1. Schematic representation of FFT output and its periodic extension. The block in the upper righthand corner comprising 64 elements represents the 64 points generated by an FFT of an 8 x 8 array. Each number in this subarray may be converted to the indices for a given spectral component by inserting a comma between the two digits, e.g., 00 is (0,0), 43 is (4,3), etc.

7,0, while the number 57 refers to 5,7, etc. Equivalently, the number 70 gives the octal location (decimal 56) of the element in question for a unidimensional storage (0/63), e.g., $\hat{a}(0,0)$ is found in location 0, $\hat{a}(2,6)$ is in decimal location 22, and $\hat{a}(7,7)$ is in decimal location 63.

3.2.2 Wave Number Spectra

The need for computing wave number spectra or some variant thereof arises from the fact that we wish to insensitize the classifier to the orientation of a given cloud pattern. In Sikula (1974), and also apparently from his computer program, the wave number spectral components are computed as the sums of spectral amplitudes ($|\hat{a}(n,m)|$) for those elements falling within corresponding annular bands in the frequency plane. Each band is one unit in width and symmetrically disposed radially about integer multiples of the radial "fundamental" frequency 1/T . That is, at least for n,m < N/2, compute

$$p = \left\lfloor \sqrt{n^2 + m^2} + .5 \right\rfloor \tag{4}$$

where extracts the greatest integer not exceeding the expression witnin, and add $|\hat{a}(n,m)|$ to the pth wave number. For $n \geq N/2$, or $m \geq N/2$, or $n,m \geq N/2$, there is some question as to what actual procedure was used. It is important to note, however, that wave numbers computed from FFT indices directly are not referenced to the principal part of the (aliased) spectrum when either index exceeds the Nyquist frequency. Consequently, direct use of Equation 4 and elimination of those spectral components for which $p > N/2$ (or worse, $p \geq N/2$), will eliminate much useful data, particularly those components in the second and fourth quadrants, as can be seen in Figure 1 (e.g., $\hat{a}(2,5)$, $\hat{a}(6,3)$.

To properly compute wave number spectra as sums over annular regions, we subtract any given index from N if it exceeds N/2:

$$n' = \min(n,N-1) \tag{5}$$

$$m' = \min(m,N-m) \tag{6}$$

where min( ) extracts the smaller of the two volumes within the parenthesis.

Equation (4) may then be applied to n' and m' to determine the proper total wave number. Here, we are merely exploiting the periodic nature of the FFT and representing n and m by their values within the principle part of the spectrum ($|f_x| \leq N/2, |f_y| \leq N/2$). Although we require this shifted data to fall within the Nyquist region or principle spectral part, this requirement <u>does not</u> simply limit the useful range of p to $p \leq N/2$, since it is clear that $f_x = f_y = N/2$ yields $p = \frac{\sqrt{2}}{2} N$. In essence, aliasing occurs above frequencies given by the square region constraint ($|f_x|$, $|f_y| \leq N/2$) and not by any equivalent one-dimensional constraint on p. Thus, we ultimately use the NxN spectral components of the first quadrant, i.e., <u>all</u> the FFT data, but combine their magnitudes based on first applying Equations (5) and (6), and then Equation (4).

Using Sikula's method described above, magnitudes of spectral components summed within annular bands become wave number spectra. Booth (1973) used various sums of normalized power spectral components as his wave number spectra. The actual normalization used by Booth is not explicitly given. Our approach, while similar in spirit to these two, differs numerically because: 1) we compute the root mean square (rms) value of the amplitude of those spectral components in each band (equivalently, the square root of the average power), and 2) all components of the two dimensional spectrum are utilized. One problem with using sums rather than averages for wave number spectra, which will arise (as it does in Sikula's data) when power spectral covariance data are not used to scale the spectra (see below), is that meaningless fluctuations are incorporated in the wave number spectra due solely to the manner in which points on a Cartesian grid fall within the annular spectral bands. A second problem, again mitigated by the use of covariance data, is that summing over annular bands emphasizes high spatial frequencies and distorts the spectrum in a manner akin to differentiating the input data. While there are arguments on both sides of this issue, we suggest that averaging rather than summing produces spectra of greater intuitive and diagnostic value. Figures 2 and 3 serve to illustrate this point.

Figure 2 shows wave number spectra for these cases, with data taken directly from Sikula's report. Case I is reported as broken low level cloudiness, Case II as small scale cumulus and Case III is labeled wispy cirrus. From a textural standpoint, images in the report show Case II to contain many small cloud elements, Case I to contain many small and several large elements, and Case III to be of a slightly mottled but mostly uniform nature. Replotting the data after dividing each summed wave number spectral component by the number of terms that were used in the sum, we have converted Sikula's data to average wave number spectra, as shown in Figure 3. These are not rms values because we do not know the individual data values within each

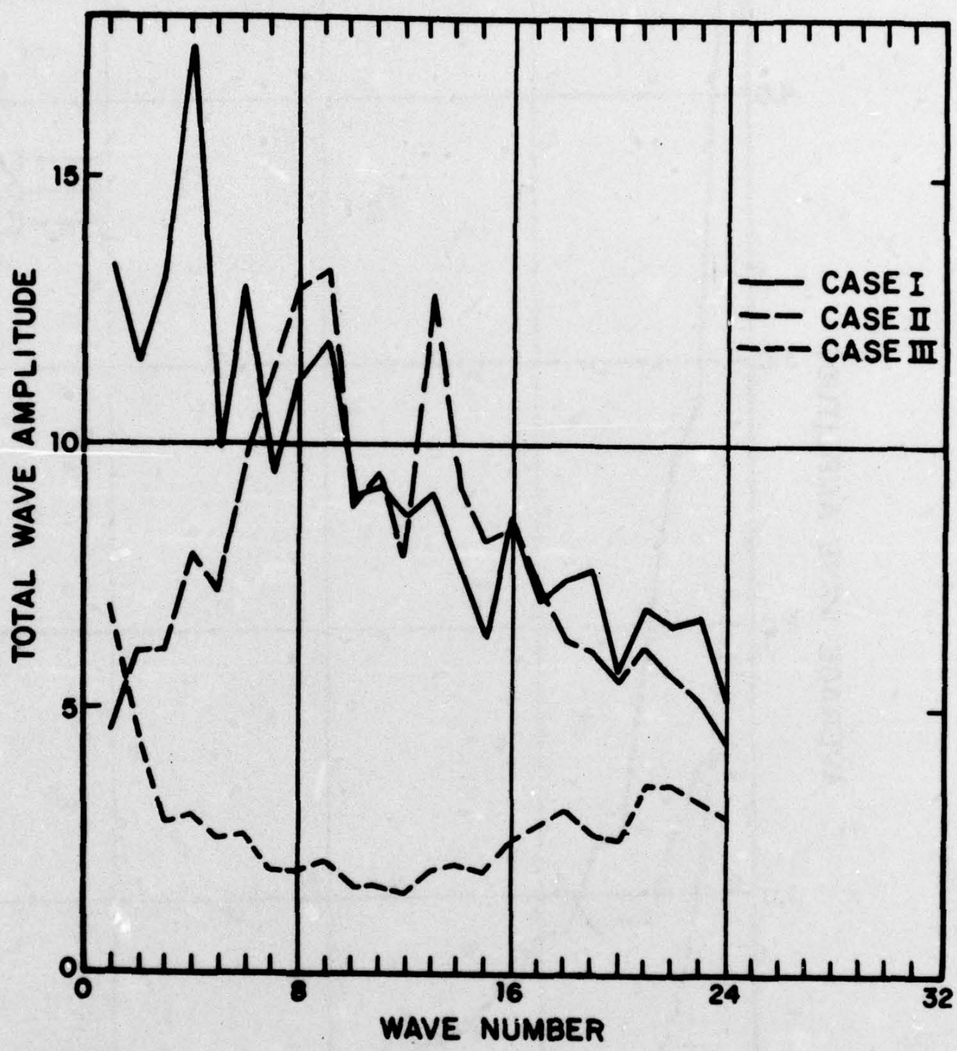

Figure 2. Three wave number spectra, after Sikula (1974).

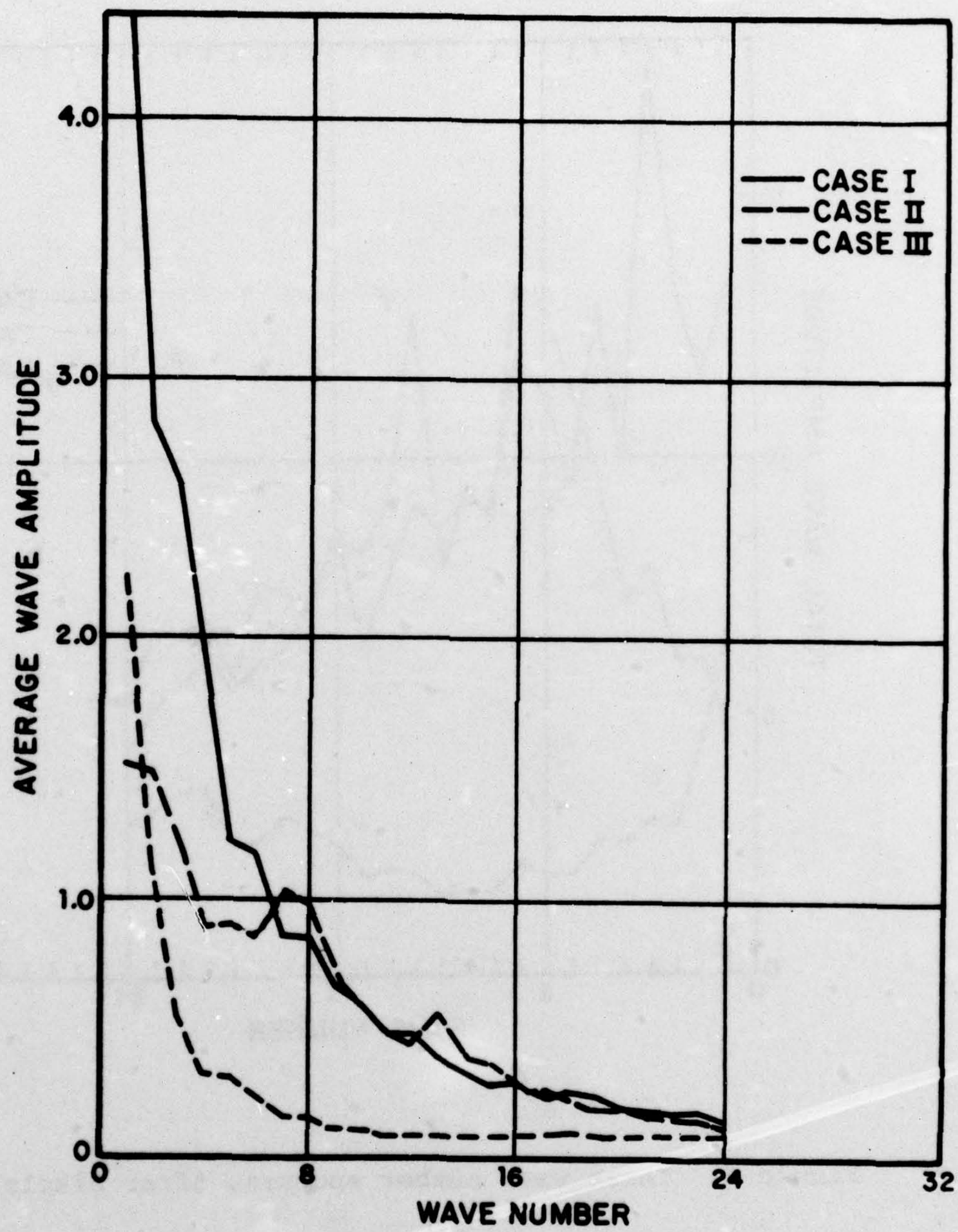

Figure 3. Three wave number spectra modified from Sikula's data. Total wave amplitude has been normalized by the number of terms in each wave number sum.

band, but only their sum. In addition to a great increase in smoothness, all the curves of Figure 3 evidence a general low pass characteristic we most often would expect to see in the spectra of clouds and other similar textures. Note that the spectra shown in Figure 3 are easily understood in terms of the imagery. That is, the spectrum of Case I is consistent with a mixture of small and large elements, Case II is consistent with small elements, and Case III indicates little textural variation beyond wave number four. In fact, for Case III it appears plausible that the spectral constancy above wave number ten is not a direct function of the cloud condition but is indicative of spectrally white system noise. Comparing wave number spectra for Cases I and II, we see a strong similarity for spectral components above wave number six which is reinforced by a corresponding similarity in the small cloud elements of the two images.

3.2.3 Classification of Cloud Types

Converting radiometric data to wave number spectra is a data reduction process which can also be thought of as producing spectral features for input to a classifier. In Pickett and Blackman (1976)we briefly treat linear discriminant classifiers as particularizations of the more general quadratic discriminant classifier and related to the concept of minimum distance. Considering wave number spectra as features and treating the class conditional probability densities for the feature vectors as multivariate normal, we have (see Duda and Hart, 1973, for example)

$$g_i(\underline{a}) = -\frac{1}{2}(\underline{a} - \underline{\mu}_i)^t \Sigma_i^{-1}(\underline{a} - \mu_i) - \frac{1}{2}\log|\Sigma_i| + \log P(c_i) \tag{7}$$

Here, $\underline{a}$ is the feature vector (wave number spectra alone or in concert with first order statistical measures), "t" denotes matrix transpose, $g_i(\underline{a})$ the discriminant for the ith class, $\underline{\mu}_i$ the mean vector for that class, $P(c_i)$ the <u>a priori</u> probability of ith class occurrence, and Σ the covariance matrix with elements given by

$$\sigma_{jk} = E[(a_j - \mu_j)(a_k - \mu_k)] \tag{8}$$

The operator E[ ] is the expectation with respect to the ensemble. Expanding Equation (7) yields

$$g_i(\underline{a}) = -\frac{1}{2}\,\underline{a}^t\,\Sigma_i^{-1}\,\underline{a} + (\Sigma_i^{-1}\,\mu_i)^t\,\underline{a} + \theta_i \qquad (9)$$

with

$$\theta_i = -\frac{1}{2}\,\underline{\mu}_i^t\,\Sigma_i^{-1}\,\underline{\mu}_i - \frac{1}{2}\log|\Sigma_i| + \log P(c_i) \qquad (10)$$

The general form of Equation (9) indicates quadratic discriminant functions.

In our prior report, we note that if Σ_i is equal to $\sigma^2 I$ (I the identity matrix), or even if Σ_i is the same for all classes (=Σ, say), then the discriminant surfaces are hyperplanes and the discriminants are linear. To construct linear discriminants, Booth used the average of the covariance matrices for all classes as the covariance matrix for each class. However, we are not so much interested in linearizing the classification procedure as we are in simplifying the computations. Since we need to compute θ_i once for each class and can compute once and store $(\Sigma_i^{-1}\,\underline{\mu}_i)^t$ as a new vector $\underline{\mu}_i'$ for each class, the potential computational complexity resides in the first term on the righthand side of Equation 9. While in general, an NxN matrix will require N^2+N multiplications and a similar number of additions (for each class), if Σ_i is a diagonal matrix we can scale each element of $\underline{a}$ by its class conditional standard deviation and compute the norm of the scaled vector. This latter computation will require only 2N multiplications and N additions for each class, which should hardly be noticed when added to the FFT and wave number computations. Assuming or even forcing a diagonal form for Σ_i is quite reasonable, given the asymptotically independent nature of power spectral estimates and the fact that the data window has no spectral leakage at the FFT frequencies, i.e., the data window does not introduce dependence between different spectral components. Thus while it would be nice if all class conditional covariance matrices are approximately equivalent to each other, this condition is not required for rapid classification. Accepting the covariance matrices as they are rather than averaging them (or ignoring them) should enhance the accuracy of the classification procedure.

3.3 Processing Cloud Image Data

During the later stages of this program, as the capability to compute wave number spectra was developed at AFGL, we attempted to perform a pilot study on selected weather imagery. Unfortunately, the images available were from display tapes and represented only HR data. Also, while three areas were selected containing mixed stratus and strato cumulus in the first, stratus or fog, in the second, and cumulus and cumulosnimbus in the third, difficulty in reading the Cu-Cb area on the tape left us with two areas containing somewhat similar basic cloud types. It was decided, therefore, to use the two data sets as a means to test and debug programs and, hopefully, to demonstrate several of the elements of the spectral analysis-classification scheme. Actual classification was not performed because: (1) the computer programs, although straightforward, have not been written, (2)climatology data, required for Bayesian classification, were not yet available, and (3) using data from mixed and overlapping cloud types as a training set is not simple nor recommended.

3.3.1 Average Wave Number Spectra

Figure 4 shows average wave number spectra for each of two regions, comprising 64 1/8 mesh boxes, i.e., a whole mesh box. Consequently, the FFT's are computed on 8x8 arrays and wave number spectra are produced for wave numbers up to six ($6 \leq 4\sqrt{2} + .5 \leq 7$). Normalization of all data has been set so that the average value is the d.c. (zero frequency) component. If classifications were to proceed from this point using these data sets for training purposes, then the d.c. component would strongly dominate the classification procedure. However, if we use the sample standard deviations for the wave number spectra, computed for each data set at each wave number, a different situation emerges. In Figure 5, we have plotted the ratios of wave number spectra to standard deviation. Note that the relative importance of the d.c. component diminishes greatly, particularly for the case representing stratus or fog.

Returning to Figure 4, we see little detail in either wave number spectrum apart from the disparity between the d.c. component and components at wave numbers one through six. Since VHR data were not available to allow an investigation of higher spatial frequencies, we computed two FFT's, one for the 64x64 array representing the stratus-stratocumulus region, and the second representing the stratus-fog region; these data are shown in Figure 6. Note that wave number eight in this figure corresponds roughly to wave number one in Figures 4 and 5. Exact correspondence is not expected because additional spectral

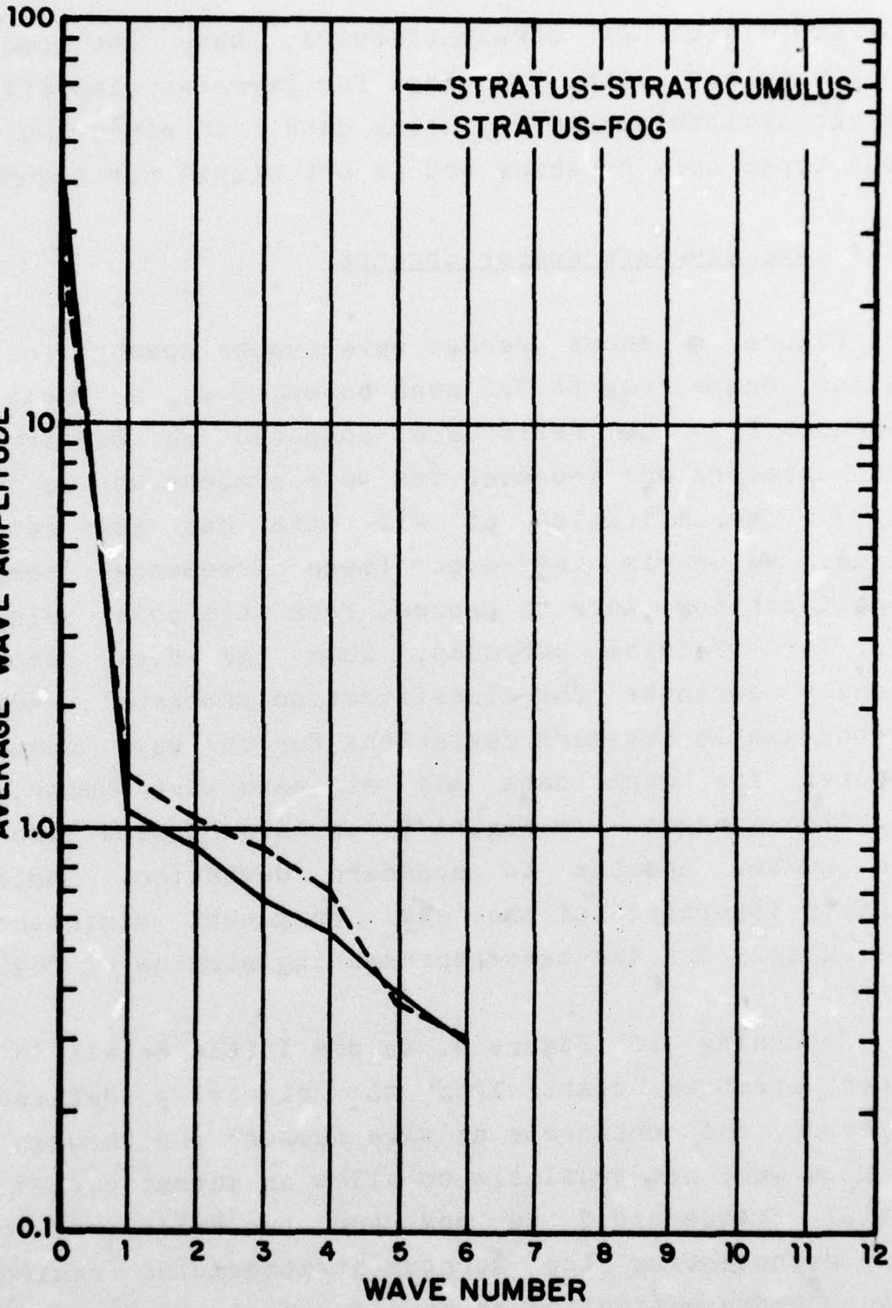

Figure 4. Wave number spectra from two whole mesh boxes. Each spectrum represents the average of 64 8 x 8 spectra of HR data.

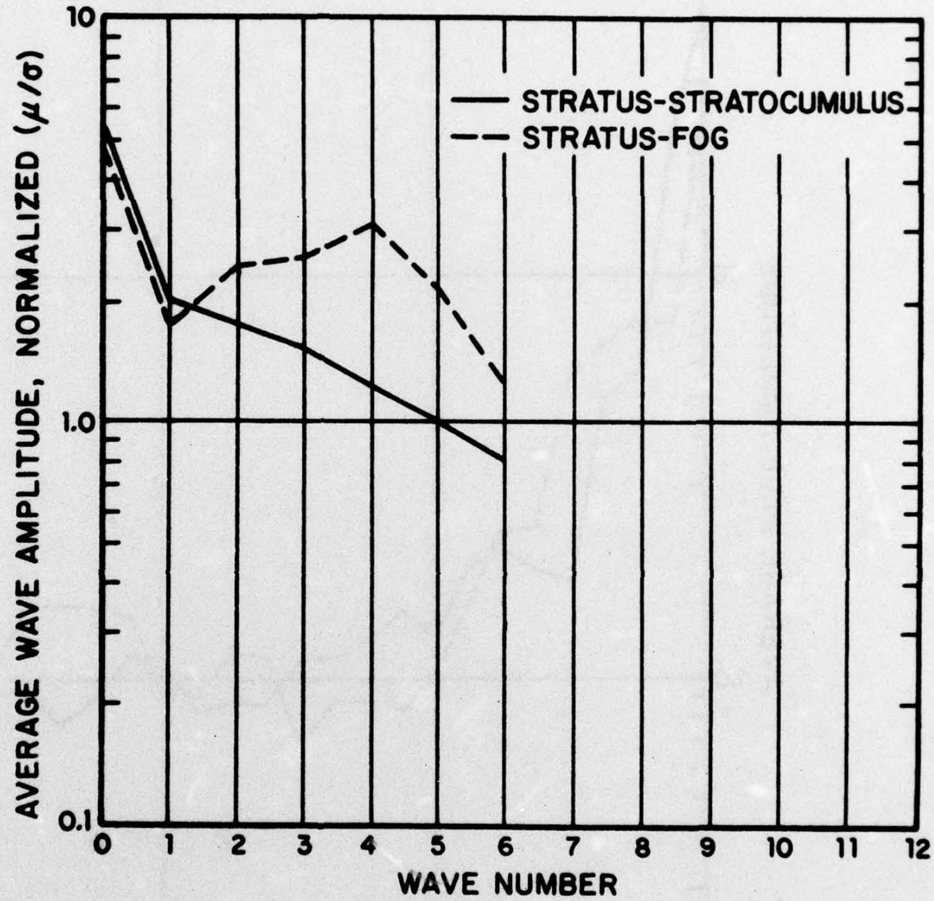

Figure 5. Wave number spectra from two whole mesh boxes normalized by class conditional standard deviations. Each spectrum is the average of 64 8 x 8 spectra from HR data.

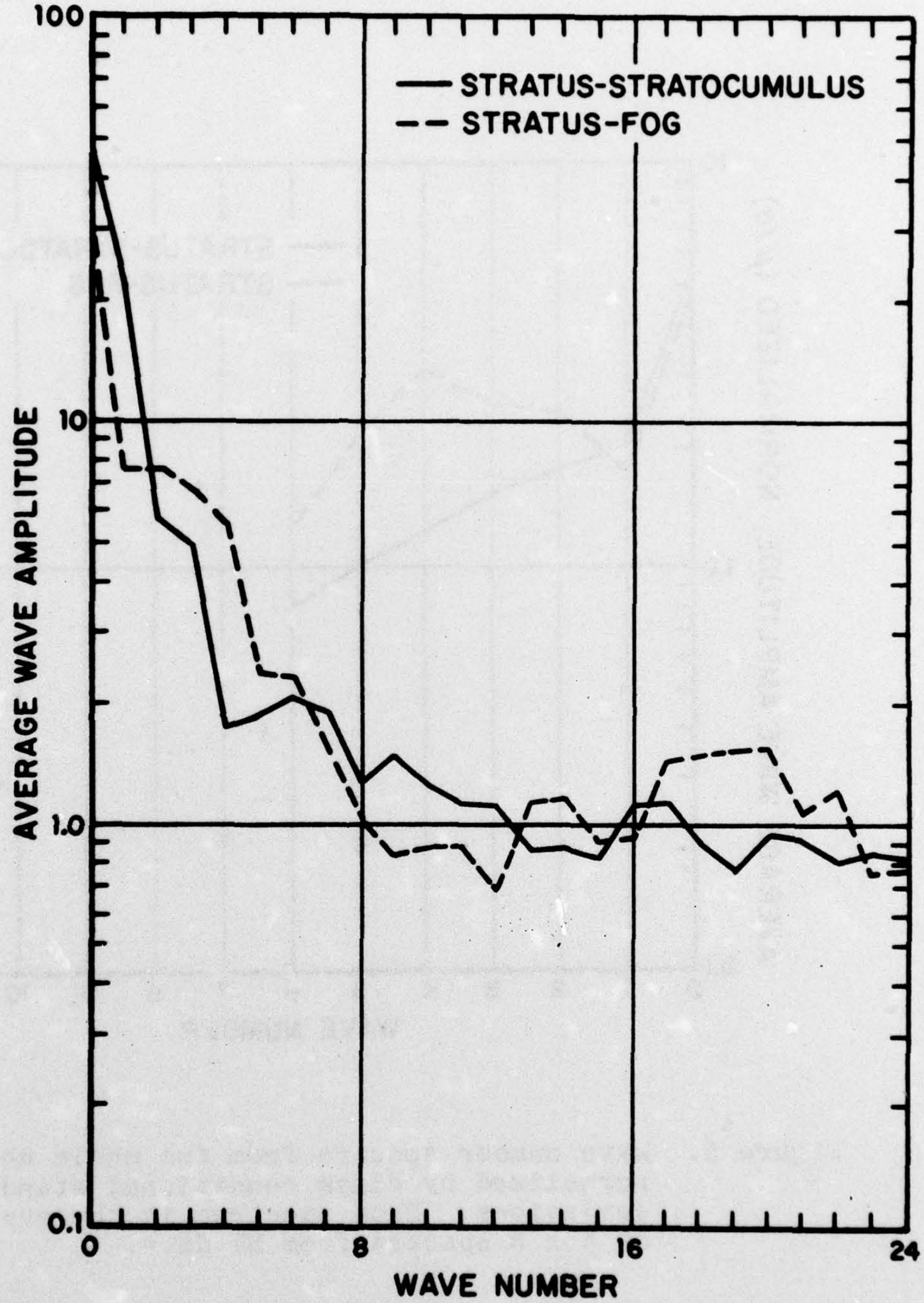

Figure 6. Wave number spectra from two whole mesh boxes. Each spectrum is from one 64 x 64 array.

components from different orientations and frequencies contribute to the average for the 64x64 based wave number spectra. To compute the spectra of Figure 6 and scale them to provide correspondence with the spectra of Figure 4, a multiplier of eight was introduced. This brings up the normalization dichotomy mentioned above. Setting the d.c. value to the array average and using the same factor to normalize the wave number spectra ignores the factor T^2 which should also be applied as a multiplier to the power spectral components. Without this factor and except for the d.c. which remains the average over the window, wave number spectra will decrease as the number of terms in the FFT increases. However, if we multiply all components of the power spectrum by T^2, then the d.c. component will increase as the number of terms increases, even though other spectral components may fluctuate about the same general level. Rather than consider alternative normalizations, or combine the two mentioned above, it is easily seen that use of the variance data as in Figure 5 resolves the problem, since whatever scale factor is used will appear in both the spectral component and its standard deviation and so be cancelled in the ratio.

While there are obviously more details in the spectra of Figure 6 than in the corresponding spectra of Figure 4, the former are not exceedingly more useful than the latter. From the low wave number behavior in Figure 6, it appears that the stratus-stratocumulus region may represent a predominantly uniform coverage, whereas the flattening of the stratus-fog spectrum towards low wave numbers indicates that the 64x64 array (whole mesh box) encompasses several correlation intervals. Unfortunately, absence of data with sufficient resolution (VHR data) makes high frequency distinctions mere conjecture. In any spectral analysis, there is no substitute for adequate spectral and spatial resolution.

3.4 Summary of Results

Since the completion and acceptance of our R&D Design and Evaluation Report (Pickett and Blackman, 1976), we have supported AFGWC in developing the capability to compute wave number spectra for cloud classification. Towards this end, we have: (1) aided the FFT implementation, (2) developed a modified wave number spectrum formulation, (3) recast and evaluated certain of Sikula's data (Sikula, 1973) in terms of this modified form, (4) directed the processing of HR data from display tapes to test programs and demonstrate feasibility, and (5) established an approach to be used in the development of a classifier based on wave number spectra. In this last regard, computation of the FFT, and conversion to wave number spectra produces spectral features; quadratic discriminants using a diagonal covariance matrix will classify the data into cloud types. Every effort must be made to ensure the generation of a properly labeled truth set of images, because the success of the classifier will depend heavily on the accuracy with which class conditional means and variances are estimated.

4. CONCLUSIONS AND RECOMMENDATIONS

The following conclusions and recommendations were developed in the course of this contract and are discussed in detail in one or the other of the two reports:

(1) Further studies are needed to establish the full range of need for imagery processing at AFGWC, particularly with respect to automating imagery processing now done visually.

(2) A long term strategy that provides for an evolutionary approach to full automation needs to be developed. Development of an image processing system with interactive capability will probably be required to provide a basis for monitoring and documenting visual processing as a first step in that evolutionary process.

(3) Inadequacies at the feature abstraction stage in the present 3DNEPH program warrant immediate attention.

(4) In the absence of detailed understanding of what features should be abstracted, spectral analysis is the most promising approach to adopt, both from the standpoint of efficiency of feature abstraction and robustness of the abstracted information.

(5) To advance demonstrations of the feasibility of spectral analysis beyond what was achieved analytically in this program, a large scale empirical study is required.

5.0 REFERENCES

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